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Modeling and estimation of the natural gas consumption for residential and commercial sectors in Iran

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ABSTRACT

In this paper, a logistic based approach is used to forecast the natural gas consumption for residential as well as commercial sectors in Iran. This approach is relatively simple compared with other forecasting approaches. To make this approach even simpler, two different methods are proposed to estimate the logistic parameters. The first method is based on the concept of the nonlinear programming (NLP) and the second one is based on genetic algorithm (GA). The forecast implemented in this paper is based on yearly and seasonal consumptions. In some unusual situations, such as abnormal temperature changes, the forecasting error is as high as 8.76%. Although this error might seem high, one does not need to be deeply concerned about the overall results since these unusual situations could be filtered out to yield more reliable predictions. In general, the overall results obtained using NLP and GA approaches are as well as or even in some cases better than the results obtained using some older approaches such as Cavallini's. These two approaches along with the gas consumption data in Iran for the previous 10 years are used to predict the consumption for the 11th, 12th, and 13th years. It is shown that the logistic approach with the use of NLP and GA yields very promising results.

1. Introduction

Natural gas is one of the most important energy sources in the world. The natural gas consumption growth has been the fastest of all the fossil fuels in recent years. While the share of oil in the world's total energy produced declined to 36.7% in 2000 from 45% in 1970, the share of natural gas has gone up to 22.8% from 17.2% for the same period. In the last 20 years, global production of natural gas has increased about 1.7 times and the US Energy Information Administration predicts its use to double by 2020 [1]. The percentage share of natural gas in marginal consumption of energy in Iran has dramatically increased in the two recent decades. Iran, a member of OPEC since 1961, is ranked amongst the world's top holders of proven oil (ranked fifth owning 8.6% of oil resources in the world) and natural gas reserves (ranked second owning 15% of natural gas resources in the world).

Because of large gas reserves in Iran and advantages of gas versus oil, the energy policy in this country is based on increase of gas/decrease of oil usage in commercial as well as residential sectors. At the first of 2007, National Iranian Gas Company (NIGC) with 440 million cubic meter refining capacity per day, had 25,000 km power transition lines and 131,320 km gas supplying network under its coverage and was providing natural gas to more than 11.6 million homes comprising of approximately 49.9 million people [2].

It should be noted that efficient use of energy resources require accurate prediction of future energy demand. Numerous researchers and practitioners have analyzed various energy issues and focused on developing appropriate energy demand models to reduce forecasting errors. Herbert [3] has analyzed monthly natural gas sales to the residential consumers in America [3]. Liu and Lin [4] have used time-series models to forecast residential natural gas consumption in Taiwan [4]. Eltony [5] has forecasted natural gas demand in Kuwait by means of econometric models [5]. Siemek [6] have estimated natural gas consumption in Poland based on the logistic curve interpretation [6]. Sarak and Satman [7] have described a deterministic model to forecast natural gas consumption for residential heating in certain areas of Turkey [7] based on previous studies performed by Durmayaz et al. [8]. Kaboudan and Liu [9] have forecasted quarterly US demand for natural gas in short term using combination of genetic programming with a two-stage least squares (2SLS) regression system of equations [9]. Aras and Aras [10] have forecasted natural gas demand for residential sector in Turkey using auto-regression approach [10].

In this paper, a logistic based approach is used to forecast the natural gas consumption for residential as well as commercial sectors in Iran. The forecast is for the 11th, 12th, and 13th year based

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on the existing data for the previous 10 years. The remainder of this paper is organized as follows. Historical reviews about sigmoid curves are presented in Section 2. Description of the logistic model is given in Section 3. In Section 4, the model is used to forecast the gas consumption in Iran. Conclusions and future research suggestions are given in Section 5.

2. Sigmoid curves and the logistic function

Sigmoid curve is a tilted *S*-shaped curve that resembles trends in the lifecycle of living things and phenomena. It is used in many different contexts such as demographics, T biology, economics, etc. In demographics and T biology contexts, sigmoid curves have been used to describe the evolution of population and in the economic context they have been used to model economic growth. The curves are used because of their ability to describe these processes and display their typical phases [11]. These curves can be considered as having a base phase, a growth phase (logarithmic growth), and a maturing phase. The maturing phase is basically the point of stabilization or zero growth rates and its value is usually referred to as the 'saturation value' (symbolized by K) or 'carrying capacity' of the environment under study. K represents the point at which the upward curve begins to level off. The *S*-shaped curve is usually summarized mathematically by the logistic equation (sigmoid curve is actually a special case of the logistic equation). A logistic equation is produced by a logistic function which is a mathematical function. The use of the logistic function to describe the population growth was first introduced by Belgian mathematician, Verhulst in the early 19th century [12]. Almost a century later, in 1920, Pearl and Reed rediscovered the logistic curve in the course of their biological study of the evolution of fly population [13]. In 1903, the French sociologist Gabriel Trade was perhaps the first to use a sigmoid curve in an economic field to analyze economic growth in relation to innovation. Other scholars have followed up Trade's ideas during the first half of the 20th century. Fisher and Pry [14] applied a logistic diffusion innovation model based on the analogy between epidemic spread and information circulation [14]. Similar research was also adopted by scholars such as Blackman [15]. Sigmoid curves have also been applied to model market demand analysis.

The logistic growth process is considered very appropriate for modeling economic growth curves. Mead and Islam [16] compare the forecasting performance of different growth curve models. They have applied 17 different models to forecast the development of telecommunication markets, represented by 25 time-series describing telephone access in 15 different countries. Their results indicate that the logistic model performs significantly better than any other growth model [16]. Sigmoid curves have been used in more recent research developments as well. Reati [17] uses both the logistic and the Gompertz curves to model the spread of technological revolutions [17]. Foster and Wild [18] show how the logistic equation can be used to model growth curves in presence of self organizational changes [18]. The logistic growth process has also been used to model economic relationships that had, for a long time, been modeled as linear forms. Honda and Suzuki [19] for instance, estimated an investment function by applying the logistic model. Their results strongly supported the use of a logistic model to estimate investment functions which appeared to follow nonlinear relationships rather than linear ones [19]. Aoki and Yoshikawa [20] have captured the role of demand as a limiting growth using logistic curves to describe the time utility of the new products [20]. Kejak et al. [21] has employed the logistic model to test the relationship between the education sector and human capital formation [21]. The logistic model has been indeed very effective in forecasting models of many different contexts however as a drawback, it has the characteristic of underestimating the forecasts in many situations [22]. NIGC has very useful information regarding daily natural gas consumption in Iran during different month of the year for different years [23]. In this article, using yearly and seasonal natural-gas consumption data in Iran for the period 1995–2005 obtained from NIGC main office in Tehran, we have proposed a logistic function that predicts or forecasts the yearly and seasonal gas consumption for the years 2006–2008.

3. The proposed procedure

The procedure is mainly based on logistic type function for estimation and a proper optimization technique like NLP or GA to minimize the error difference between the model and the actual data. The proposed function is of the following from:

$$\frac{dc(t)}{dt} = rc(t)\left(1 - \frac{c(t)}{K}\right) \tag{1}$$

where t is time, $c(t)$ is the natural gas consumption for any given time, and r and K are positive constants defined as the growth rate and the carrying capacity, respectively. We will later elaborate on why K is defined as carrying capacity. Using separation of variables it can be shown that the solution of the above logistic equation is given by

$$c(t) = \frac{K}{1 + Me^{-rt}} \tag{2}$$

where M is an arbitrary constant. To solve for M, let us denote the inflection point of $c(t)$ by t_0 and set the second derivative of $c(t)$ equal to zero at $t = t_0$. It can be shown that the second derivative of $c(t)$ with respect to t is given by:

$$c''(t) = \frac{MKr^2e^{rt}(M - e^{rt})}{(M + e^{rt})^3} \tag{3}$$

Therefore, by setting $c''(t_0) = 0$, one will obtain

$$M = e^{rt_0} \tag{4}$$

Substitution of (4) into (2) leads to the following:

$$c(t) = \frac{K}{1 + e^{-r(t-t_0)}} \tag{5}$$

It should be noted from (5) that the consumption, $c(t)$, approaches K (saturation level) as $t \to \infty$. This is the reason why K is defined as carrying capacity. It should also be noted that by estimating the logistic parameters, t_0, r, and K, the consumption could be forecasted. Therefore, the objective is to estimate the above logistic parameters such that for a given set of n data points the error given by the following equation is minimized.

$$e = \sum_{i=1}^{n} (c(t_i) - c_i)^2 \tag{6}$$

In (6), the term c_i is the actual consumption at time t_i and the term $(c(t_i) - c_i)^2$ is the squared error made at the time instant t_i. The following constraints will be used to minimize (6):

$$\begin{array}{ll} K, t_0, r > 0 & \text{(i)} \\ t_1 < t_0 < t_n & \text{(ii)} \\ K > \max\{c_i\} & \text{(iii)} \end{array} \tag{7}$$

The optimization technique used by Cavallini has the drawback that it may not yield a satisfactory result on the first try and consequently one may have to use different initial guesses to achieve an adequate result [24]. In this paper, we use two different procedures that will not have the above problem. The first procedure is based on NLP and the second one is based on GA. In both NLP and

GA optimization approaches, like any other optimization approach, the objective is to minimize a given cost function subject to certain constraints. The cost function and the constraint considered here are given by (6) and (7), respectively.

In the world of mathematics, NLP is the process of solving a system of equalities and inequalities called constraints, over a set of unknown real variables, along with a cost function (also called objective function or energy function) to be either minimized or maximized based on the problem requirements. In NLP, some of the constraints and/or the cost function are nonlinear. Mathematically, an NLP problem can be stated as minimizing or maximizing a cost function $F(x)$ subject to certain constraints given by the following

$$\begin{aligned} &g_i(x) = 0 \quad i = 1, 2, \ldots, p;\ p \geqslant 0 \\ &h_j(x) \geqslant 0 \quad j = p+1, p+2, \ldots, q;\ q > p \end{aligned} \tag{8}$$

That is, there is one scalar-valued function $F(x)$ (objective function), of several variables (x here is a vector), that is to be minimized or maximized subject to one or more constraints. This is indeed the problem under the consideration in this article.

GA on the other hand is a very effective way of quickly finding a reasonable solution to a complex problem. It is a general purpose search algorithm based on the principles of evolution observed in nature that can be applied to a wide variety of optimization problems. GA is most effective in a search space for which little is known. The search usually begins with an initial population of individuals (typically randomly generated) and then, interactively, evaluates the individuals in the population for fitness with respect to the problem environment and performs genetic operations on various individuals in the population to produce a new population. In this process, GA combines selection, crossover, and mutation operators with the objective of finding the best solution to a problem. GA continues the search for this optimal solution until a specified termination criterion is met [25]. In summary, GA consists of the following three steps: (1) creating an initial population, (2) evaluating the fitness of each individual in the population, (3) repeating the process until termination (either a time limit or when a sufficient fitness is achieved).

There are different routines available in ''MATLAB Optimization Toolbox'' that can solve variety of constrained and unconstrained nonlinear optimization problems. Among these routines are NLP and GA. These are indeed the routines used in this paper, for different data sets, to minimize the cost function given by (6) subject to the constraints given by (7). The results are presented in the next section.

Table 1
Optimal logistic parameters obtained by NLP and GA methods for residential consumption.

Interval	NLP method parameters			GA method parameters		
	K	r	t_0	K	r	t_0
Year	2893.2000	0.1453	10.0000	2893.0000	0.1453	10.0000
Spring	512.2031	0.1417	9.5914	512.7032	0.1417	10.0000
Summer	175.7564	0.3309	1.8570	175.7714	0.3309	1.8570
Autumn	539.4592	0.1991	5.5782	546.2740	0.1991	5.5782
Winter	1251.0000	0.1520	9.9883	1248.0000	0.1520	10.0000

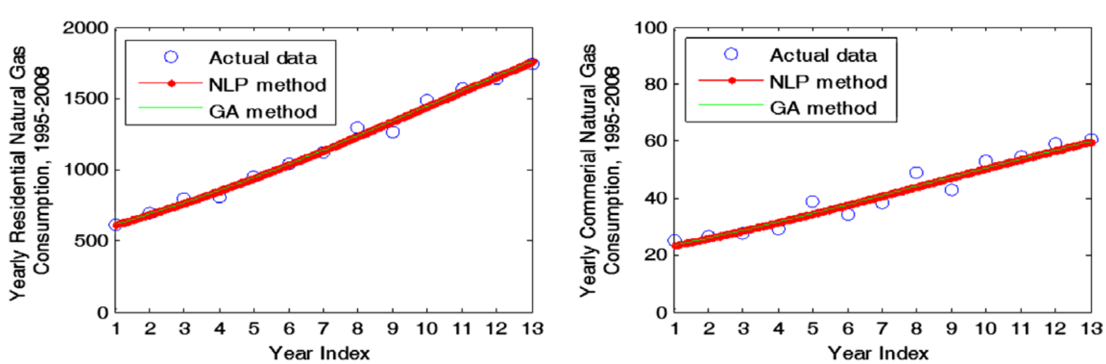
Table 2
Optimal logistic parameters obtained by NLP and GA methods for commercial consumption.

Interval	NLP method parameters			GA method parameters		
	K	r	t_0	K	r	t_0
Year	91.4301	0.1417	8.4923	91.4291	0.1418	8.4923
Spring	10.2654	0.1776	3.1136	10.4734	0.1776	3.4155
Summer	6.7479	0.3391	2.1074	6.7479	0.3391	2.1074
Autumn	21.8757	0.1690	7.1102	22.1693	0.1690	7.1102
Winter	28.6793	0.2122	4.7115	28.4688	0.2122	4.6989

4. Application of the model to natural gas consumption in Iran

From the data that was obtained from NIGC, it was recognized that the natural gas consumption in residential/commercial sectors in Iran had a logistic curve characteristic. Using this fact, a logistic function of the form (2) is used to model yearly and seasonal consumption based on the actual yearly and seasonal data for the years 1995–2005. Then, using both NLP and GA optimization techniques, the optimal logistic parameters (shown in Tables 1 and 2) and consequently the estimate of the yearly and seasonal gas consumptions for the years 2006, 2007, and 2008 were obtained. From the data shown in Tables 1 and 2, it is important to note the calculated optimal logistic parameters are extremely close for both NLP and GA methods. As a result, one expects that the NLP and the GA graphs to have very similar characteristics which is indeed the case (see Figs. 1–5).

Table 3 shows the actual and estimated yearly natural gas consumption using NLP and GA approaches for both residential as well as commercial sectors in Iran based on the parameters given in Tables 1 and 2. Fig. 1 shows the graph corresponding to the data given in Table 3. The actual and estimated seasonal consumption data for the same time interval are given in Tables 4–7 and the corresponding graphs are shown in Figs. 2–5, respectively.



(a)- Residential (b)- Commercial

Fig. 1. Yearly natural gas consumption vs. year index from 3/21/1995 to 3/20/2008.

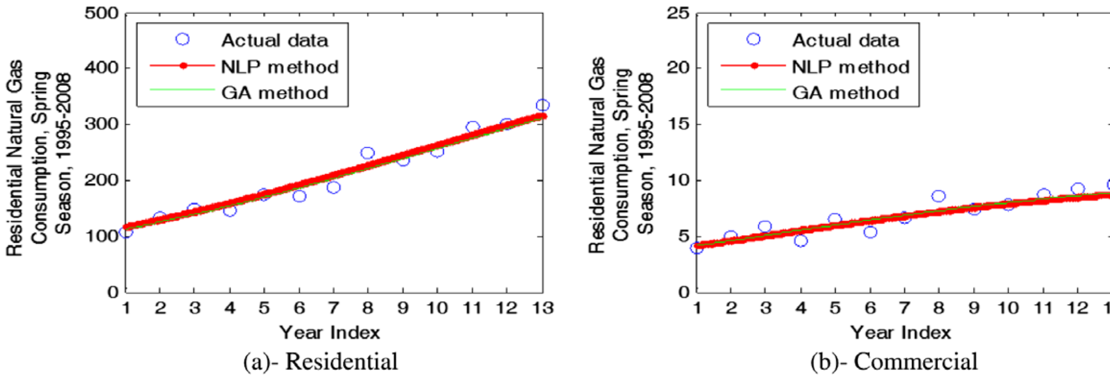


Fig. 2. Spring natural gas consumption vs. year index from 3/21/1995 to 3/20/2008.

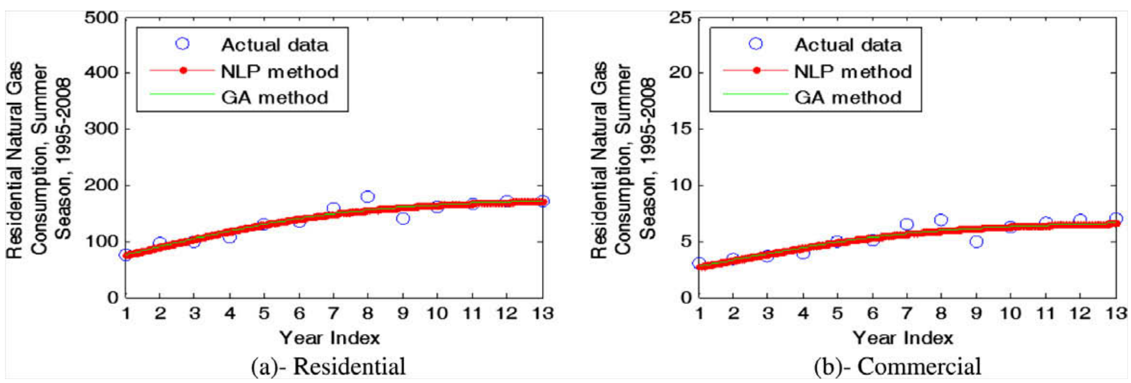


Fig. 3. Summer natural gas consumption vs. year index from 3/21/1995 to 3/20/2008.

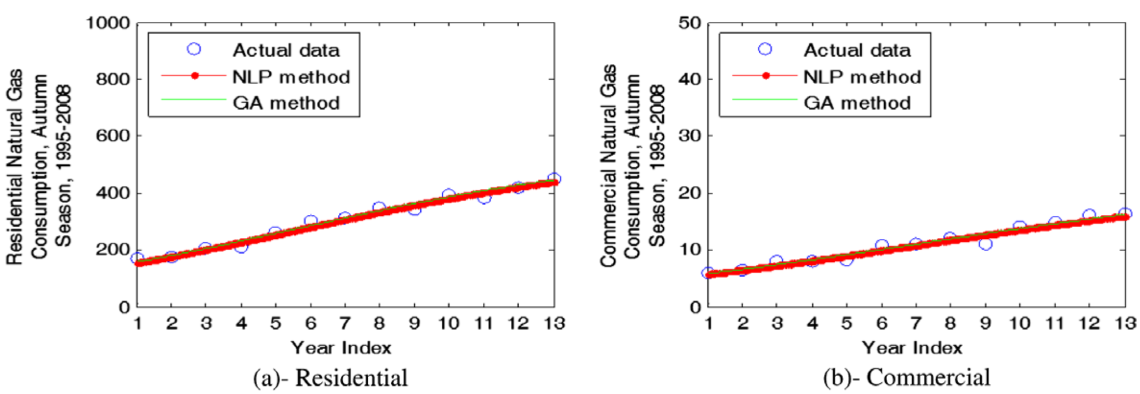


Fig. 4. Autumn natural gas consumption vs. year index from 3/21/1995 to 3/20/2008.

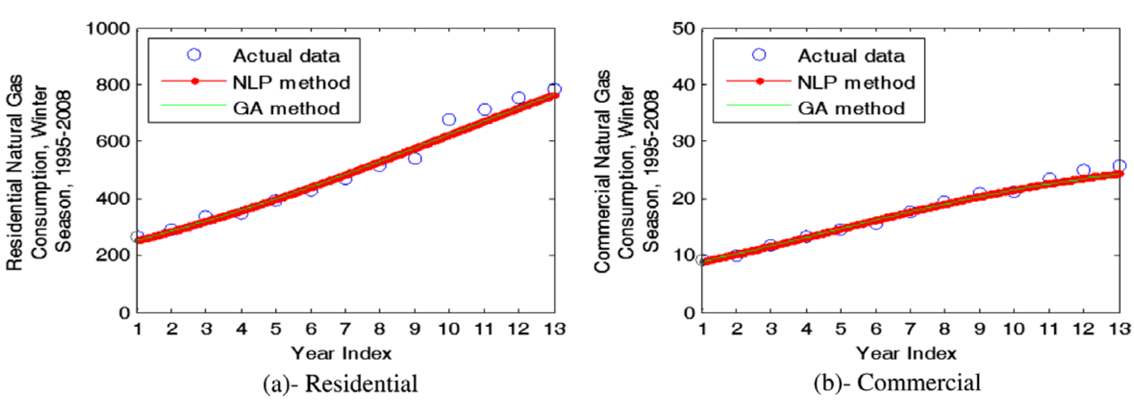


Fig. 5. Winter natural gas consumption vs. year index from 3/21/1995 to 3/20/2008.

Table 3
Actual and estimated yearly natural gas consumption.

Year index	Year	Residential natural gas consumption (million m^3)			Commercial natural gas consumption (million m^3)		
		Actual data	NLP model	GA model	Actual data	NLP model	GA model
1	3/21/1995–3/20/1996	618.1	615.9	615.9	24.9210	23.4969	23.4835
2	3/21/1996–3/20/1997	691.4	689.3	689.3	26.8413	26.0545	26.0421
3	3/21/1997–3/20/1998	792.5	768.4	768.4	27.7257	28.7726	28.7615
4	3/21/1998–3/20/1999	808.0	853.1	853.1	29.2144	31.6371	31.6274
5	3/21/1999–3/20/2000	953.9	943.1	943.1	38.6508	34.6291	34.6212
6	3/21/2000–3/20/2001	1041.4	1037.7	1037.7	34.4163	37.7256	37.7196
7	3/21/2001–3/20/2002	1126.4	1136.2	1136.2	38.4235	40.8996	40.8957
8	3/21/2002–3/20/2003	1292.5	1237.9	1237.9	49.1219	44.1212	44.1196
9	3/21/2003–3/20/2004	1261.7	1341.7	1341.7	42.8451	47.3587	47.3594
10	3/21/2004–3/20/2005	1482.7	1446.6	1446.6	53.2873	50.5799	50.5827
11	3/21/2005–3/20/2006	1566.6	1551.5	1551.5	54.5299	53.7529	53.7578
12	3/21/2006–3/20/2007	1636.1	1655.3	1655.0	58.9652	56.8479	56.8548
13	3/21/2007–3/20/2008	1738.7	1757.0	1757.0	60.7500	59.8460	59.8480

Table 4
Actual and estimated Spring season natural gas consumption.

Year index	Year	Residential natural gas consumption (million m^3)			Commercial natural gas consumption (million m^3)		
		Actual data	NLP model	GA model	Actual data	NLP model	GA model
1	3/21/1995–3/20/1996	108.0270	116.9842	111.9500	3.8730	4.1805	4.1304
2	3/21/1996–3/20/1997	132.9800	130.2637	124.8425	4.9200	4.6268	4.5819
3	3/21/1997–3/20/1998	147.3873	144.4995	138.7058	5.8127	5.0809	5.0436
4	3/21/1998–3/20/1999	144.6357	159.6408	153.4994	4.5643	5.5359	5.5083
5	3/21/1999–3/20/2000	173.4184	175.6109	169.1572	6.4816	5.9845	5.9687
6	3/21/2000–3/20/2001	171.0193	192.3072	185.5869	5.3807	6.4202	6.4179
7	3/21/2001–3/20/2002	185.9254	209.6024	202.6710	6.5746	6.8369	6.8495
8	3/21/2002–3/20/2003	249.1830	227.3477	220.2688	8.5170	7.2298	7.2581
9	3/21/2003–3/20/2004	236.3543	245.3770	238.2206	7.4457	7.5953	7.6398
10	3/21/2004–3/20/2005	252.4519	263.5134	256.3528	7.8481	7.9310	7.9916
11	3/21/2005–3/20/2006	293.8927	281.5758	274.4851	8.7073	8.2358	8.3121
12	3/21/2006–3/20/2007	301.3395	299.3858	292.4369	9.1605	8.5095	8.6009
13	3/21/2007–3/20/2008	334.3065	316.7749	310.0347	9.5935	8.7532	8.8586

Table 5
Actual and estimated Summer season natural gas consumption.

Year index	Year	Residential natural gas consumption (million m^3)			Commercial natural gas consumption (million m^3)		
		Actual data	NLP model	GA model	Actual data	NLP model	GA model
1	3/21/1995–3/20/1996	76.2954	75.5007	75.5072	3.0046	2.7478	2.7478
2	3/21/1996–3/20/1997	97.5270	89.9570	89.9646	3.4730	3.3125	3.3125
3	3/21/1997–3/20/1998	100.1688	104.3015	104.3104	3.6312	3.8807	3.8807
4	3/21/1998–3/20/1999	107.8100	117.7931	117.8031	3.8900	4.4209	4.4209
5	3/21/1999–3/20/2000	129.6959	129.8583	129.8693	4.9041	4.9076	4.9076
6	3/21/2000–3/20/2001	134.5652	140.1708	140.1827	5.0348	5.3253	5.3253
7	3/21/2001–3/20/2002	158.2738	148.6499	148.6625	6.5262	5.6690	5.6690
8	3/21/2002–3/20/2003	179.5498	155.4020	155.4153	6.9502	5.9422	5.9422
9	3/21/2003–3/20/2004	141.5015	160.6432	160.6569	4.9985	6.1535	6.1535
10	3/21/2004–3/20/2005	162.0942	164.6315	164.6455	6.3058	6.3135	6.3135
11	3/21/2005–3/20/2006	166.3465	167.6205	167.6348	6.6535	6.4326	6.4326
12	3/21/2006–3/20/2007	170.3045	169.8354	169.8499	6.8955	6.5202	6.5202
13	3/21/2007–3/20/2008	172.1514	171.4627	171.4773	7.0486	6.5841	6.5841

The residential and commercial percent errors using NLP and GA methods for the years 2006, 2007, and 2008 using an optimal logistic function based on the data for the years 1995–2005 are shown in Table 8. The largest percent errors, for different time intervals, for the residential sector as well as commercial sector are highlighted in bold. As can be seen from the table, the largest yearly percent error for residential sector is less than 1.2% for both NLP and GA methods and it is less than 3.6% for the commercial sector. These are indeed fairly reasonable and acceptable results. From the same table, it can be seen that for the residential sector the largest percent errors are less than 7.3%, 0.8%, 6.0%, and 6.1% for Spring, Summer, Autumn, and Winter season, respectively. Also, for the commercial sector, the largest percent errors are less than 8.8%, 6.6%, 5.7%, and 6.1% for Spring, Summer, Autumn, and Winter season, respectively. In general, these results are all within reasonable ranges and fairly acceptable although it is explained in the next section the reason for large percent errors.

Table 6
Actual and estimated Autumn season natural gas consumption.

Year index	Year	Residential natural gas consumption (million m^3)			Commercial natural gas consumption (million m^3)		
		Actual data	NLP model	GA model	Actual data	NLP model	GA model
1	3/21/1995–3/20/1996	168.3337	154.6570	156.6107	5.8663	5.7440	5.8211
2	3/21/1996–3/20/1997	173.1743	177.5168	179.7593	6.5257	6.4880	6.5750
3	3/21/1997–3/20/1998	205.0814	201.9820	204.5335	7.9186	7.2847	7.3825
4	3/21/1998–3/20/1999	209.6611	227.6977	230.5741	8.0389	8.1270	8.2367
5	3/21/1999–3/20/2000	259.3470	254.2211	257.4326	8.2530	9.0070	9.1288
6	3/21/2000–3/20/2001	302.4775	281.0489	284.5993	10.8225	9.9140	10.0478
7	3/21/2001–3/20/2002	310.4345	307.6543	311.5407	11.0655	10.8360	10.9814
8	3/21/2002–3/20/2003	348.8948	333.5275	337.7408	12.1052	11.7587	11.9165
9	3/21/2003–3/20/2004	341.0930	358.2141	362.7393	11.1070	12.6698	12.8398
10	3/21/2004–3/20/2005	394.6776	381.3443	386.1617	14.0224	13.5569	13.7388
11	3/21/2005–3/20/2006	384.8179	402.6500	407.7365	14.7821	14.4089	14.6023
12	3/21/2006–3/20/2007	416.6673	421.9693	427.2999	16.1327	15.2165	15.4207
13	3/21/2007–3/20/2008	451.1420	439.2395	444.7883	16.2580	15.9725	16.1869

Table 7
Actual and estimated Winter season natural gas consumption.

Year index	Year	Residential natural gas consumption (million m^3)			Commercial natural gas consumption (million m^3)		
		Actual data	NLP model	GA model	Actual data	NLP model	GA model
1	3/21/1995–3/20/1996	268.4040	254.2420	253.2731	9.1960	8.9677	8.9182
2	3/21/1996–3/20/1997	289.5735	286.4220	285.3441	10.0265	10.3244	10.2662
3	3/21/1997–3/20/1998	338.3493	321.3630	320.1691	11.8507	11.7640	11.6960
4	3/21/1998–3/20/1999	345.3923	358.9800	357.6653	13.2077	13.2592	13.1808
5	3/21/1999–3/20/2000	395.8039	399.1090	397.6705	14.6961	14.7784	14.6890
6	3/21/2000–3/20/2001	430.9472	441.5049	439.9394	15.5528	16.2879	16.1870
7	3/21/2001–3/20/2002	468.4438	485.8352	484.1431	17.5562	17.7546	17.6422
8	3/21/2002–3/20/2003	517.0438	531.6931	529.8758	19.3562	19.1493	19.0256
9	3/21/2003–3/20/2004	541.0514	578.6063	576.6671	20.9486	20.4485	20.3139
10	3/21/2004–3/20/2005	677.5277	626.0562	624.0000	21.0723	21.6357	21.4910
11	3/21/2005–3/20/2006	714.5541	673.4996	671.3329	23.5459	22.7017	22.5476
12	3/21/2006–3/20/2007	752.3113	720.3940	718.1242	24.9887	23.6439	23.4814
13	3/21/2007–3/20/2008	783.8510	766.2213	763.8569	25.8490	24.4652	24.2952

Table 8
Residential and commercial percent error using NLP and GA methods, 2006–2008.

Time interval	Residential percent error						Commercial percent error					
	NLP method			GA method			NLP method			GA method		
	2006	2007	2008	2006	2007	2008	2006	2007	2008	2006	2007	2008
Yearly	−0.96	**1.17**	1.05	−0.96	1.16	1.05	−1.42	**−3.59**	−1.49	−1.42	−3.58	−1.48
Spring	−4.19	−0.65	−5.24	−6.60	−2.95	**−7.26**	−5.41	−7.11	**−8.76**	−4.54	−6.11	−7.66
Summer	**0.77**	−0.28	−0.4	**0.77**	−0.27	−0.39	−3.32	−5.44	**−6.59**	−3.32	−5.44	**−6.59**
Autumn	4.63	1.27	−2.64	**−5.96**	−2.55	−1.41	−2.52	**−5.68**	−1.76	−1.22	−4.41	−0.44
Winter	−5.75	−4.24	−2.25	**−6.05**	−4.54	−2.55	−3.59	−5.38	−5.35	−4.24	**−6.03**	−6.01

5. Conclusions

In this paper, a logistic based approach is used to forecast the natural gas consumption in Iran for the 11th, 12th, and 13th year based on the data available for the previous 10 years. The percent residential and commercial errors for yearly and seasonal consumptions using NLP and GA methods are shown in Table 8. As can be seen from entries of the table, the error has exceeded 8% for the Spring season using NLP method. This is the case for which there has been some unusual temperature drop in climate. Since this is an abnormal situation that cannot be foreseen ahead of time, one does not need to be deeply concerned with this particular result. For the case under the study, even this much error does not cause any imperative problem since the production capacity is much higher than the actual demand. One way to reduce error in situations like these is to make our forecast dependent on the temperature and perhaps some other parameters as well. This is left for future research. Furthermore, when dealing with overall results, the unusual situations could be filtered out to yield more reliable prediction. One last thing to note from Table 8 is that the consumption obtained using either NLP or GA methods are fairly close to the actual consumption. This in fact justifies the modeling of residential and commercial natural gas consumption in Iran using a logistic function.

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